

Analysis of Multidimensional Poverty Indicators in Indonesia with Association Rules

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<i>Artikel Info</i>	<i>Abstrak</i>
<p><i>Article history:</i> Received September 08, 2020 Revised November 25, 2020 Accepted December 10, 2020 Available online December 21, 2020</p> <p>Keywords: <i>Association Rules; MCA; Poverty Indicators</i></p> <p>JEL Classification; I30; Q12</p>	<p><i>This study was conducted to find patterns of relationships between 14 multidimensional poverty indicators in Indonesia from 2015-2019. To provide a more specific description of the relationship pattern, association rules with the apriori algorithm is used as the analysis method. The preprocessing stage to transform data was carried out using fuzzy functions and data reduction with Multiple Correspondence Analysis (MCA) to support the association analysis process. The results obtained are 15 relationship patterns or rules between items from the multidimensional poverty indicator with a support value of 60%-80% and 100% confidence. This means that the relationship pattern is significantly formed from objects with a strong relationship between the items and can represent poverty records in the last five years. The relationship pattern consists of four combinations of things. Suppose there is a high category decrease in the percentage of poor people indicator, a low category decrease in the open unemployment indicator, a high category increase in the percentage of households indicator according to the source of lighting from electricity, and a low category increase in the percentage indicator of households according to the broadest wall, not bamboo / other. In that case, there is a reduction in multidimensional poverty in Indonesia.</i></p>

INTRODUCTION

Two-thirds of the world's population lives on less than \$ 10 per day, and every ten people live below the extreme poverty line, according to the World Bank, with an income level of less than \$ 1.90 per day (World Bank, 2017). Poverty has traditionally been defined as a lack of money. BPS also measures poverty from a monetary approach using the poverty line through the basic consumption approach (basic need), which is calculated into a standard such as the National Poverty Line (IDR 454,652 / capita/month) (BPS, March 2020). However, the poor themselves consider their poverty experience much broader than conditions of lack of money, such as income. Therefore, no undeniable that poverty from time to time becomes more complicated. The measurement of poverty based solely on the monetary dimension me come up with a lot of criticism (Bappenas, 2018).

Amartya Sen (1980 in Bappenas, 2018) has criticized the poverty approach through monetary analysis. According to Amartya, poverty is not only related to purchasing power parity, income/consumption, but there are other dimensions such as education, health, quality of life, democracy, and people's freedom of economic access. Poverty is reflected when some of the population cannot access primary education or essential health services as a result of financial inability. Likewise, the quality of living standards such as

houses with dirt floors, lack of proper sanitation, energy sources for lighting, and improper cooking. Therefore, a multidimensional poverty measurement has been developed to create a more comprehensive picture (Artha and Dartanto, 2014).

Faced with the problem of poverty, the terms poverty alleviation and poverty reduction have developed. Changes in the concept of "poverty alleviation" to "poverty reduction" (Syahyuti, 2014). Poverty reduction is related to policies to reduce the number and percentage of poor people or the severity of poverty's impact on the poor's lives.

That is why the Sustainable Development Goals (SDGs) explicitly include multidimensional poverty reduction targets. The target is listed in SDGs Indicator 1.2.2, by 2030 (to) reduce at least half of the proportion of men, women, and children of all ages living in poverty in all its dimensions, according to national definitions (United Nations, 2020). In 2010, the Oxford Poverty and Human Development (Ophi) and United Nations Development (UNDP) to develop the Multidimensional Poverty Index (MPI) or Poverty Index Multidimensional (HPI) for the first time through the analysis of the Human Development Report (HDR) (Alkire et al., 2014).

Nationally, the government has compiled the Master Plan for the Acceleration and Expansion of Indonesian Poverty Reduction (MP3KI). In MP3KI using MPI (Multidimensional Poverty Index) as one of the programs, when comparing the MPI - measured by various indicators that have been modified with the National Poverty Line Indonesia in 2014, MPI is more generous (79, 6 million people) than the National Poverty Line (27, 73 million people) (Budiantoro et al., 2016). From the data above, if measured by several dimensions, not just one size, poverty in Indonesia gives results that are even higher than the average MPI Global 108 countries in 2014 (14, 8 million people).

Indonesia is a country that is rich in diversity, has different social and cultural cultures. It does not rule out that the indicators that affect poverty also vary; this then becomes the government's attention in taking the right steps and policies by the root causes of poverty problems in Indonesia. Therefore, multidimensional indicators need to be seen about poverty in Indonesia to compare poverty from various aspects/dimensions, overcome future poverty problems, and provide recommendations to the government from different perspectives.

In the research by Winda Aprianti et al. (2017), an analysis of Tanah Laut District's multidimensional poverty indicators has been carried out. The method of analysis used is association rules with the apriori algorithm. The transformation of the multifaceted poverty indicator data into a set of items is carried out using the fuzzy membership function at the data preprocessing stage. This study indicates that the relationship patterns or rules between objects of the multidimensional poverty indicators cannot be explicitly concluded or

the relationship patterns formed are numerous. This is because the relationship pattern began still involves items from the multidimensional poverty indicator with a minimal appearance value, so it is necessary to reduce items as a preprocessing stage to get more specific conclusions. Methods of Principal Component Analysis (PCA) are usually used to reduce the data, but this method is used if the data metrics (KemalBay & Korkmazoglu, 2014). For categorical data, the Multiple Correspondence Analysis (MCA) method is used; as stated in Greenacre (2017), MCA can be called categorical PCA data that maximizes variance in all cases.

Thus, this study was conducted to look for patterns of relationships between Indonesia's multidimensional poverty indicators in 2015-2019. The analysis method is association rules with the apriori algorithm, with the minimum value parameters of support and confidence. The data preprocessing stage was carried out, namely data transformation with the fuzzy membership function and data reduction with MCA, to support the association analysis process. This study can provide a more specific description of the pattern of relationships between multidimensional poverty indicators.

This research is expected to be able to provide benefits, both theoretically and practically. Theoretically, it is expected to provide new knowledge about the pattern of relationships between multidimensional poverty indicators in Indonesia using the association rules method with the apriori algorithm. Meanwhile, practically it is expected to provide recommendations to the government regarding multidimensional poverty indicators that significantly affect poverty reduction in Indonesia.

RESEARCH METHODS

Data Used

The data used is secondary data from the publication of the Central Statistics Agency (BPS). This study's multidimensional poverty indicators consist of 14 social and economic indicators in Indonesia from 2014 to 2019. The following are multidimensional poverty indicators used in this study:

Table 1. Multidimensional poverty indicators

Indicator	Information
X1	Net Enrollment Rate (NER) SMA / SMK / MA / Package C (%)
X2	Literacy Rate for Population Ages 15-24 Years (%)
X3	Gross Enrollment Rate (APK) of Children Attending Early Childhood Education (%)
X4	Percentage of Poor Population (%)
X5	GDP at Current Price (Billion Rupiah)
X6	GDP at Constant Prices (Billion Rupiah)
X7	Open Unemployment (people)
X8	Percentage of Households by Main Cooking Fuel (%)
X9	Percentage of Households with Access to Proper Sanitation (%)
X10	Percentage of Households by Decent Drinking Water Source (%)
X11	Percentage of Households by Source of Lighting from Electricity (%)
X12	Percentage of Households by Widest Roof Non-Fiber / Other (%)
X13	Percentage of Households by Widest Floor Not Land (%)
X14	Percentage of Households by Widest Wall Not Bamboo / Others (%)

Data analysis technique

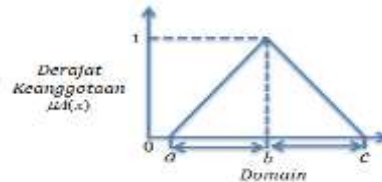
This research begins with preprocessing data, which consists of transformation data with fuzzy membership functions and data reduction with Multiple Correspondence Analysis (MCA), then continued with association rules. Data transformation is carried out to change the form of data according to the subsequent data mining process; in this research, data transformation is carried out by changing the multidimensional poverty dataset in the form of numerical data into itemset in the form of categorical data (Brian & Sanwidi, 2018). Data reduction reduces or reduces the number of items in research; this process can be done by selecting or compressing fewer items (Pramana et al., 2018).

Fuzzy Membership Function

The fuzzy membership function is converting the exact or ideal value of an element x into a membership function with membership values in the interval $[0,1]$ (Hagan, 2006). Some of the membership function Fuzzy commonly used is the function of a triangle as in Figure 1 (Arafat & Mukhlash, 2015). This function is defined by three parameters, namely the smallest domain value when the slightest degree of membership (a), the enormous degree of membership in the domain (b), and the most considerable domain

value when the smallest degree of membership (c) with a mathematical equation such as equation 1.

Figure 1. Representation of the triangle curve



$$\text{Triangle}(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \dots\dots\dots(1)$$

with the degree of fuzzy membership written as in equation (2)

$$\mu(x) = \begin{cases} 0, & x \leq a \text{ atau } x \geq c \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \end{cases} \dots\dots\dots(2)$$

Multiple Correspondence Analysis (MCA)

Greenacre (2006) states that if the correspondence analysis (CA) algorithm is commonly applied to the indicator matrix or the Burt matrix, this method is called multiple correspondence analysis (MCA) or multiple correspondence analysis. The indicator matrix is a matrix that shows the presence of each respondent's category or case (Kalayci & Basaran, 2014). The indicator matrix element is a binary element that is only worth 0 or 1, where the value 0 represents absent while the value 1 represents the present. The Burt matrix is obtained from the cross-tabulation of the indicator matrix combined with the categorical variables. The rows and columns of all the original variables can be analyzed. This MCA's output will display the most critical variables contributing the most to explaining variations in data sets (Natarajan et al., 2020).

Association Rules

Analysis of association rules is also often referred to as market basket analysis. To decide whether an association rule is essential or not, it can be determined through two parameters, namely support (value of the asset) and confidence (certainty value). Support is the percentage of item combinations in the database, and faith is the strong relationship between items in the association rules (Kaur & Kang, 2016).

Priori algorithm is a type of association rule in market basket analysis. The technique of working on the apriori algorithm is divided into several stages, called iteration (Tanna & Ghodasara, 2014). Each iteration produces a high-frequency pattern of the same length starting from the first iteration, which has a high-frequency design of one size. This first iteration supports each item

calculated by reading the database (Ginting et al., 2018) after the support is selected as a high-frequency pattern with a length of 1 or often called a 1-item set. Up to the iteration k, which produces a high-frequency way of length k. The iteration-k support of each item is also calculated by reading the database. After license is selected as a high-frequency pattern of length k or often called k-itemset. The abbreviation k-itemset means a set of k-items (Rani et al., 2014).

RESULT AND DISCUSSION

Data Transformation

The dataset consisting of 14 numerical indicators was transformed into categories. The data category consists of 7 types, using the fuzzy membership function. The following is a multidimensional poverty dataset:

Table 2. Multidimensional Poverty Indicator Values 2014-2019

Indikator	Tahun					
	2014	2015	2016	2017	2018	2019
X1	59,35	59,71	59,95	60,37	60,67	60,84
X2	99,68	99,67	99,67	99,66	99,71	99,76
X3	29,31	35,18	34,62	33,84	37,92	36,93
X4	10,96	11,13	10,7	10,12	9,66	9,22
X5	8,91E+11	8,61E+11	9,32E+11	1,02E+12	1,04E+12	1,12E+12
X6	9,42E+11	9,88E+11	1,04E+12	1,09E+12	1,15E+12	1,20E+12
X7	7244905	7454767	7024172	7005262	6871264	6816840
X8	29,97	24,64	21,76	17,51	16,49	14,13
X9	61,08	62,14	67,8	67,89	69,27	77,39
X10	68,38	70,97	71,14	72,04	73,68	89,27
X11	97,01	97,54	97,62	98,14	98,51	98,85
X12	97,66	98	98,26	98,48	98,67	88,54
X13	92,8	93,1	93,58	94,38	94,79	95,46
X14	91,35	96,14	97,14	97,58	97,63	97,95

Source: BPS

Before categorizing the data with the fuzzy membership function, we need to classify ("Increase," "Decrease," or "Fixed") and calculate the percentage change in indicator value, which is obtained from the ratio between the difference in indicator values from the previous year and the highest difference between each indicator.

Table 3. Classification of Indicator Value Changes from the Previous Year

Indicator	Year				
	2015	2016	2017	2018	2019
X1	Ride	Ride	Ride	Ride	Ride
X2	Down	Permanent	Down	Ride	Ride
X3	Ride	Down	Down	Ride	Down
X4	Ride	Down	Down	Down	Down
X5	Down	Ride	Ride	Ride	Ride
X6	Ride	Ride	Ride	Ride	Ride
X7	Ride	Down	Down	Down	Down
X8	Down	Down	Down	Down	Down
X9	Ride	Ride	Ride	Ride	Ride
X10	Ride	Ride	Ride	Ride	Ride
X11	Ride	Ride	Ride	Ride	Ride
X12	Ride	Ride	Ride	Ride	Down
X13	Ride	Ride	Ride	Ride	Ride
X14	Ride	Ride	Ride	Ride	Ride

Table 4. Percentage Change in Indicator Value from the Previous Year

Indicator	Year				
	2015	2016	2017	2018	2019
X1	85.71	57.14	100	71.43	40.48
X2	20	0	20	100	100
X3	100	9,54	13.29	69.51	16.87
X4	29.31	74.14	100	79.31	75.86
X5	35.78	84.81	100	31.79	91.89
X6	79.73	86.3	91.31	97.83	100
X7	48.74	100	4.39	31.12	12.64
X8	100	54.03	79.74	19.14	44.28
X9	13.07	69.79	1.02	17.1	100
X10	16.64	1.08	5.76	10.55	100
X11	100	15.81	97.4	69.81	64.45
X12	3.36	2.54	2,2	1.88	100
X13	37.73	60.96	100	51.56	83.73
X14	100	20.95	9,11	1.04	6.61

Fuzzy Membership Function

Then the fuzzification process is carried out with the triangular curve fuzzy membership function from the percentage change in the indicator value (as x) into seven categories, namely Low Increase (NR), Medium Increase (NS), High Increase (NT), Fixed (T), Low Decrease (TR), Medium Decrease (TS), High Decrease (TT). An increase or decrease is categorized as low if the x-value is between 0 - 33.33%, moderate if the x value is between 33.33 - 66.67%, and it is classified as high if the x value is 66.67%. The fuzzy membership function formula as follows:

The membership function for the Low Rise (NR) category is as in equation (3):

$$\mu_{NR}(x) = \begin{cases} 1, & x \leq 33.33 \\ \frac{40-x}{6.67}, & 33.33 < x < 40 \\ 0, & x \geq 40 \end{cases} \dots\dots\dots(3)$$

The membership function for the Medium Ascending (NS) category is as in equation (4):

$$\mu_{NS}(x) = \begin{cases} 0, & x \leq 33.33 \\ \frac{x-33.33}{16.67}, & 33.33 \leq x < 50 \\ \frac{66.67-x}{16.67}, & 50 < x < 66.67 \\ 0, & x \geq 66.67 \end{cases} \dots\dots\dots(4)$$

The membership function for the High Rise (NT) category is as in equation (5):

$$\mu_{NT}(x) = \begin{cases} 0, & x \leq 33.33 \\ \frac{x-60}{6.67}, & 60 < x < 66.67 \\ 1, & x \geq 66.67 \end{cases} \dots\dots\dots(5)$$

Meanwhile, if the results of the data difference show a decrease, then use the equation:

The membership function for the Lower Low (TR) category is as in equation (8):

$$\mu_{TR}(x) = \begin{cases} 1, & x \geq -33.33 \\ \frac{x+40}{6.67}, & -40 < x < -33.33 \\ 0, & x \leq -40 \end{cases} \dots\dots\dots(6)$$

The membership function for the Lower Medium (TS) category is as in equation (7):

$$\mu_{TS}(x) = \begin{cases} 0, & x \geq -33.33 \\ \frac{-x-33.33}{16.67}, & -50 \leq x < -33.33 \\ \frac{x+66.67}{16.67}, & -66.67 < x < -50 \\ 0, & x \leq -66.67 \end{cases} \dots\dots\dots(7)$$

The membership function for the Lower High (TT) category is as in equation (8):

$$\mu_{TT}(x) = \begin{cases} 0, & x \geq -33.33 \\ \frac{x+60}{6.67}, & -66.67 < x < -60 \\ 1, & x \leq -66.67 \end{cases} \dots\dots\dots(8)$$

So that we obtain the following transformed dataset :

Table 5. Dataset of Data Transformation Results

Then the dataset is formed into the *itemset* table as follows:

Indicator	Year				
	2015	2016	2017	2018	2019
X1	NT_X1	NS_X1	NT_X1	NT_X1	NS_X1
X2	TR_X2	T_X2	TR_X2	NT_X2	NT_X2
X3	NT_X3	TR_X3	TR_X3	NT_X3	TR_X3
X4	NR_X4	TT_X4	TT_X4	TT_X4	TT_X4
X5	TS_X5	NT_X5	NT_X5	NR_X5	NT_X5
X6	NT_X6	NT_X6	NT_X6	NT_X6	NT_X6
X7	NS_X7	TT_X7	TR_X7	TR_X7	TR_X7
X8	TT_X8	TS_X8	TT_X8	TR_X8	TS_X8
X9	NR_X9	NT_X9	NR_X9	NR_X9	NT_X9
X10	NR_X10	NR_X10	NR_X10	NR_X10	NT_X10
X11	NT_X11	NR_X11	NT_X11	NT_X11	NT_X11
X12	NR_X12	NR_X12	NR_X12	NR_X12	TT_X12
X13	NR_X13	NS_X13	NT_X13	NS_X13	NT_X13
X14	NT_X14	NR_X14	NR_X14	NR_X14	NR_X14

Table 6. Itemset

No.	Item	t1	t2	t3	t4	t5
1	NR_X1	0	0	0	0	0
2	NS_X1	0	1	0	0	1
3	NT_X1	1	0	1	1	0
4	T_X1	0	0	0	0	0
5	TR_X1	0	0	0	0	0
6	TS_X1	0	0	0	0	0
7	TT_X1	0	0	0	0	0
8	NR_X2	0	0	0	0	0
9	NS_X2	0	0	0	0	0
10	NT_X2	0	0	0	1	1
...
94	NT_X14	1	0	0	0	0
95	T_X14	0	0	0	0	0
96	TR_X14	0	0	0	0	0
97	TS_X14	0	0	0	0	0
98	TT_X14	0	0	0	0	0

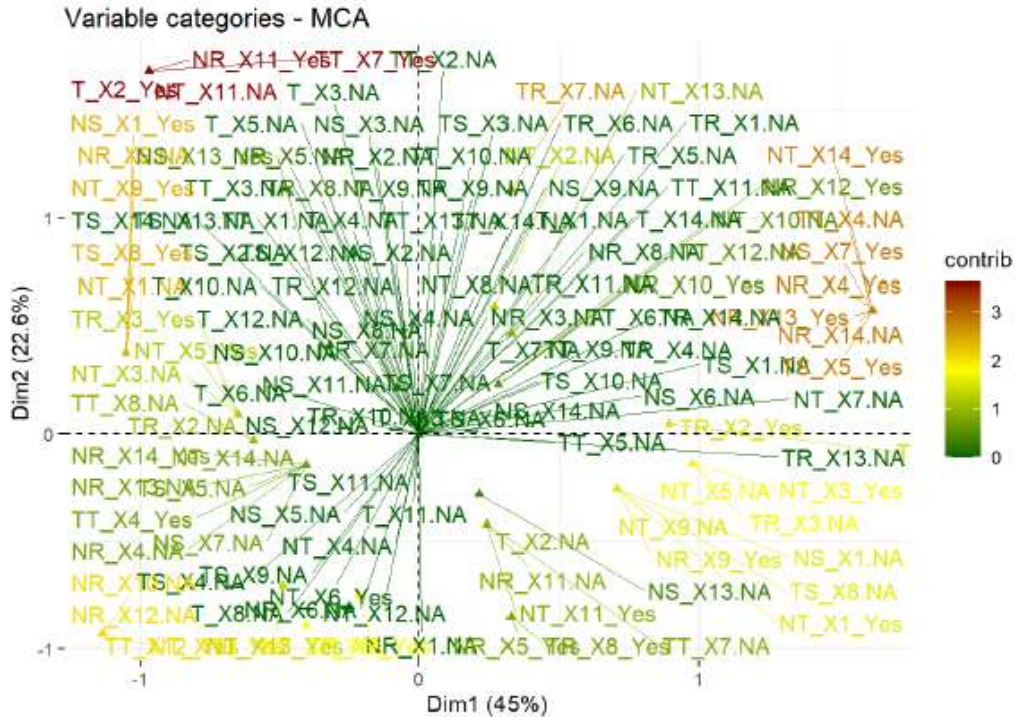
Obtained 98 items (from 14 multidimensional poverty indicators with each indicator consisting of 7 categories) with a value of "1" means the emergence of *things* from the multidimensional poverty indicator at time t and the value "0" means the absence of *items* from the multidimensional poverty indicator at time t.

Data reduction

Multiple Correspondence Analysis (MCA)

These items need to be reduced with MCA to produce more specific *rules* through *item* selection with the itemset's contribution value. Data processing using R *software* so that the MCA plot is obtained as follows:

Figure 2. The plot of MCA Itemset with R



The MCA plot results show that the item's color closer to red means that it has a more significant contribution value. The color of the thing closer to green standards that the item has a smaller contribution value. To obtain a new itemset consisting of 12 items, namely T_X2, NR_X4, TT_X4, TS_X5, NS_X7, TR_X7, TT_X7, NR_X11, NT_X11, NR_X13, NR_X14, NT_X14.

Association Rules

Apriori Algorithm

After reducing the items on the itemset using MCA, then forming rules or patterns of relationships between objects from the multidimensional poverty indicator using the apriori algorithm

Figure 3. The results of applying *association rules* with the *apriori* algorithm using R

	lhs	rhs	support	confidence	coverage	lift	count
[1]	{TR_X7}	=> {NR_X14}	0.6	1.0	0.6	1.250000	3
[2]	{TR_X7}	=> {TT_X4}	0.6	1.0	0.6	1.250000	3
[3]	{TR_X7}	=> {NT_X11}	0.6	1.0	0.6	1.250000	3
[4]	{NR_X14}	=> {TT_X4}	0.8	1.0	0.8	1.250000	4
[5]	{TT_X4}	=> {NR_X14}	0.8	1.0	0.8	1.250000	4
[6]	{NR_X14, TR_X7}	=> {TT_X4}	0.6	1.0	0.6	1.250000	3
[7]	{TR_X7, TT_X4}	=> {NR_X14}	0.6	1.0	0.6	1.250000	3
[8]	{NR_X14, TR_X7}	=> {NT_X11}	0.6	1.0	0.6	1.250000	3
[9]	{NT_X11, TR_X7}	=> {NR_X14}	0.6	1.0	0.6	1.250000	3
[10]	{NR_X14, NT_X11}	=> {TR_X7}	0.6	1.0	0.6	1.666667	3
[11]	{TR_X7, TT_X4}	=> {NT_X11}	0.6	1.0	0.6	1.250000	3
[12]	{NT_X11, TR_X7}	=> {TT_X4}	0.6	1.0	0.6	1.250000	3
[13]	{NT_X11, TT_X4}	=> {TR_X7}	0.6	1.0	0.6	1.666667	3
[14]	{NR_X14, NT_X11}	=> {TT_X4}	0.6	1.0	0.6	1.250000	3
[15]	{NT_X11, TT_X4}	=> {NR_X14}	0.6	1.0	0.6	1.250000	3

Based on the results of data processing, 15 rules of relationship (rules) between items from the poverty indicators were obtained as follows:

- ☞ If there is a low decrease in the open unemployment indicator (X7), it is possible to have an intense increase in households' percentage according to the broadest wall, not bamboo / other (X14). Also, an insufficient decrease in the open unemployment indicator (X7) allows a high reduction in the percentage of poor people indicator (X4) and a high increase in the percentage of households indicator according to the source of lighting from electricity (X11). This rule is quite significant, representing 60% of the poverty dataset for the last five years.
- ☞ Suppose there is a low increase in households' percentage indicator according to the broadest wall of non-bamboo / other (X14). In that case, it is possible to have a high decrease in the percentage of poor people indicator (X4), and vice versa; if there is a high decrease in the rate of poor people indicator (X4), it is possible for a low increase in the percentage indicator of households according to the broadest wall, not a bamboo / other (X14). This rule is quite significant, representing 80% of the poverty dataset for the last five years.
- ☞ If there is a low increase in the percentage of households indicator according to the broadest wall of non-bamboo / other (X14) and

an insufficient decrease in the open unemployment indicator (X7), it is possible to have a high reduction in the percentage of poor people indicator (X4). Also, it is possible to have a high increase in households' rate by the source of lighting from electricity (X11). This rule is quite significant, representing 60% of the poverty dataset for the last five years.

- ✎ Suppose a low decrease in the open unemployment indicator (X7) and a high reduction in poor people's percentage (X4). In that case, it is possible to have a low increase in the percentage of households indicator according to the broadest wall of non-bamboo / other (X14). It is also possible to have a high rise in households' percentage by the source of lighting from electricity (X11). This rule is quite significant, representing 60% of the poverty dataset for the last five years.
- ✎ Suppose there is a high increase in households' percentage according to the source of lighting from electricity (X11) and a low decrease in the open unemployment indicator (X7). In that case, it is possible to have an intense increase in the percentage of households indicator according to the broadest wall, not bamboo / other (X14). Also, it allows for a high decrease in the percentage of poor people (X4). This rule is quite significant, representing 60% of the poverty dataset for the last five years.
- ✎ Suppose there is a low increase in households' percentage according to the broadest wall, not a bamboo / other (X14), and a high decrease in households' rate according to the source of lighting from electricity (X11). In that case, it is possible to have a low reduction in the open unemployment indicator (X7). Also, it allows for a high decrease in the percentage of poor people arrow (X4). This rule is quite significant, representing 60% of the poverty dataset for the last five years.
- ✎ Suppose there is a high increase in households' percentage according to the source of lighting from electricity (X11) and a high decrease in the rate of poor people indicator (X4). In that case, it is possible to have a low reduction in the open unemployment indicator (X7). Also, it allows for an intense increase in the percentage of households according to the broadest wall of non-bamboo / other (X14). This rule is quite significant, representing 60% of the poverty dataset for the last five years.

CONCLUSION

There are 15 relationship patterns or rules between items from the multidimensional poverty indicator with a support value of 60% -80% and 100% confidence. That is the patterned relationship and significantly formed from objects with a strong connection between the items and can represent a record of poverty over five years. The relationship pattern consists of four combinations of things. Suppose there is a high category decrease in the percentage of poor people indicator, a low category decline in the open unemployment indicator, a high category increase in the percentage of households indicator according to the source of lighting from electricity, and a low category increase in the percentage indicator of households according to the broadest wall, not bamboo / other. In that case, there is a reduction in multidimensional poverty in Indonesia. This can illustrate indicators that significantly affect multidimensional poverty reduction in Indonesia as a recommendation to the government in making policies in poverty reduction efforts in Indonesia.

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